Locally Equivalent Weights for Bayesian MrP

Ryan Giordano, Alice Cima, Erin Hartman, Jared Murray, Avi Feller

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Standard error estimation

Does this mean anything?

Yes: We can meaningful sum these weights against regressors.

What else might it mean?

Does the spread relate to frequentist variance?

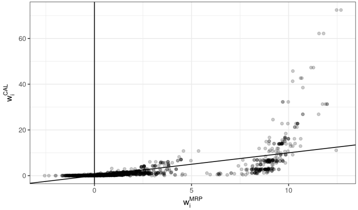

Figure 1: Comparison between raking and MrPlew weights for the Name Change dataset

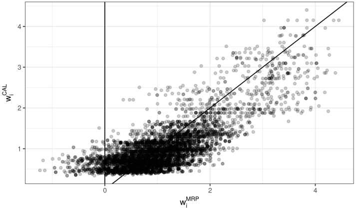

Figure 2: Comparison between raking and MrPlew weights for the Gay Marriage dataset

Standard error estimation

Standard error consistency theorm: (sketch)

For Bayesian hierarchical logictic regression, define

$$\varepsilon_n = y_n - \mathbb{E}_{\mathcal{P}(\theta|\text{Survey data})}\left[m(\mathbf{x}_n^\intercal \theta)\right] \quad \text{and} \quad \psi_n := N_S w_n^{\text{MrP}} \varepsilon_n.$$

We state mild conditions under which, as $N \to \infty$,

$$\sqrt{N}\left(\hat{\mu}_{\text{MrP}} - \mu_\infty\right) \to \mathcal{N}\left(0, V\right) \quad \text{for some } \mu_\infty \text{ and variance } V\text{, and}$$

$$\frac{1}{N_S}\sum_{i=1}^{N_S}(\psi_n - \overline{\psi})^2 \to V.$$

The use of w_n^{MrP} is exactly analogous to the use of raking weights for standard error estimation.

This builds on our earlier work on the Bayesian infinitesimal jackknife[1].

[1] **G.** and Broderick 2024.

Standard error estimation

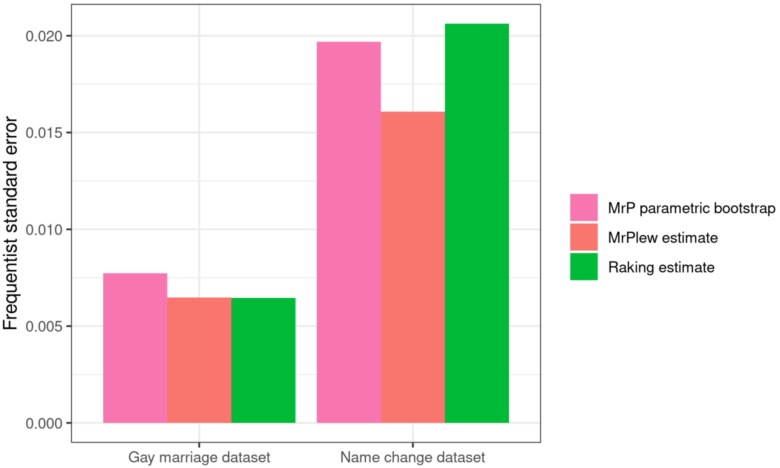

Figure 3: Frequentist standard deviation estimates

Future work

Notice that there was no discussion of misspecification!

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1. Assume your initial model was accurate
2. Select some perturbation your model should be able to capture
3. Use local sensitivity to detect whether the change is what you expect
4. If the change is not what you expect, either (1) or (2) was wrong

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Such checks recover generlized versions of many standard diagnostics for linear models.

Examples:

- Additive parameter shifts $\leftrightarrow$ Unbiasedness
- Invariance to survey data weighting $\leftrightarrow$ Regressor + residual orthogonality
- Importance sampling $\leftrightarrow$ Sandwich covariance $\stackrel{?}{=}$ Inverse Fisher information

Future work

Student contributions and ongoing work:

- **Alice Cima** contributed significantly to this work
- **Vladimir Palmin** is working on extending MrPlew to `lme4`
- **Sequoia Andrade** is working on generalizing to other local sensitivity checks
- **Lucas Schwengber** is working on novel flow–based techniques for local sensitivity
- **(Currently recruiting!)** Doubly–robust Bayesian Hierarchical MrP

Alice Cima

Vladimir Palmin

Sequoia Andrade

Lucas Schwengber

Preprint and R package (hopefully) coming soon!

References

G. and T. Broderick (2024). *The Bayesian Infinitesimal Jackknife for Variance*. arXiv: 2305.06466 [stat.ME]. URL: https://arxiv.org/abs/2305.06466.